

FACTORS INFLUENCING BIG DATA ANALYTICS ADOPTION: THE INDIAN MANAGEMENT ACCOUNTANTS' PERSPECTIVE

 Vitin Kumar^{(a)1}  Vinod Kumar Singh^(b)

^(a)Research Scholar, Faculty of Management Studies, Gurukula Kangri (Deemed to be University), Haridwar, Uttarakhand, India; E-mail: vitinkyagi@gmail.com

^(b)Professor, Faculty of Management Studies, Gurukula Kangri (Deemed to be University), Haridwar, Uttarakhand, India; E-mail: drvksingh@gkv.ac.in

ARTICLE INFO

Article History:

Received: 1st July 2026

Reviewed & Revised: 1st July 2026
to 25th September 2026

Accepted: 30th September 2026

Published: 5th October 2026

Keywords:

Big Data Analytics Adoption,
Management Accountants,
Management Accounting, Process
Innovation, Industrial and Innovation,
Value Chain Management

JEL Classification Codes:

M40, M41, M150, M490, M410

Peer-Review Model:

External peer-review was done through
Double-blind method.

ABSTRACT

With advances in computing and informatics, the management accounting domain is undergoing a strategic shift, and the role of management accountants has transformed from a strategic advisor to a strategic partner within businesses. Big data analytics (BDA) is a promising technological innovation with immense potential to improve the entire management accounting value chain. However, it involves several positive and negative factors that drive BDA adoption in real-world applications. This study investigates the influence of key factors driving the adoption of BDA by Indian cost and management accountants (CMAs) in management accounting work practices. Utilizing an online survey instrument, quantitative data from 242 respondents engaged in industry or practice were collected. The research is based on the Technology-Organization Environment (TOE) framework and uses Partial Least Squares Structural Equation Modelling (PLS-SEM) in R. The results reveal that relative advantage ($\beta = 0.428, p < 0.01$), compatibility ($\beta = 0.286, p < 0.01$) and vendor support ($\beta = 0.212, p < 0.01$) have statistically significant positive effects on BDA adoption. At the same time, complexity shows a negative but statistically insignificant association ($\beta = -0.005$) with BDA adoption. The model further demonstrates high explanatory power ($R^2 = 0.671$ and $\text{Adj } R^2 = 0.666$), without unnecessary inflation or the inclusion of variables. The outcome of this work has improved understanding of the relevant factors in the technical, organizational, and environmental dimensions of BDA adoption. It provides actionable insights for managers, management accountants, organizations, professional bodies and third parties engaged in providing BDA technology solutions, helping them tap into the enormous opportunities in BDA.

© 2026 by the authors. Licensee of the American Accounting & Finance Society, USA. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

INTRODUCTION

The advancement and diffusion of information and communication technologies have led to the generation of massive amounts of data. By virtue of volume and heterogeneous characteristics, this data is known as big data. According to the Fortune Business Insights (2025) report, the big data technology market size is projected to grow from USD 397.27 billion in 2024 to USD 1,194.35 billion by 2032, at a CAGR of 14.8%. The significance of data and the use of data-related technologies have increased manifold in accounting and related domains (Richardson et al., 2019), and companies are experiencing internal and external pressure to integrate these technologies into their business operations (Jackson et al., 2023). Digitization has reshaped the business world, and business data repositories are regarded as key corporate assets in modern definitions of business. Heterogeneity in the characteristics and speed of big data makes it difficult to process and extract meaningful insights by simply using traditional data analytics tools. Thus, unrefined big data, as raw data, cannot be used; it has to be transformed into a processable form to become a valuable asset that drives profitable activities. Over time, many business analytics techniques have been developed to facilitate data collection, analysis, and timely dissemination of information to support real- or near-real-time decision-making (Rikhardsson & Yigitbasioglu, 2018). Big data analytics (BDA) enables the extraction of meaningful insights from organizational data reservoirs, thereby improving the financial sustainability of corporates. BDA is regarded as one of the most widely implemented technologies, enabling organizations to achieve greater operational efficiency and a stronger competitive position (Akter et al., 2016; Lutfi et al., 2022). Modern database architecture can collect and analyze financial and non-financial data, enabling business managers to intervene concurrently in strategic decision-making (Munir et al., 2022). Big data analytics has become an integral part of modern

¹Corresponding author: ORCID ID: 0009-0009-6623-1841

© 2026 by the authors. Hosting by American Accounting & Finance Society. Peer review under responsibility of American Accounting & Finance Society, USA. <https://doi.org/10.46281/ijafr.v17i2.2966>

To cite this article: Kumar, V., & Singh, V. K. (2026). FACTORS INFLUENCING BIG DATA ANALYTICS ADOPTION: THE INDIAN MANAGEMENT ACCOUNTANTS' PERSPECTIVE. *International Journal of Accounting & Finance Review*, 17(2), 1-14. <https://doi.org/10.46281/ijafr.v17i2.2966>

business ecosystems, and the entire business value chain is experiencing its influence with varying magnitude. The use of big data enables improved decision-making, better learning, and greater innovation within firms. BDA enables decision-makers to gain deeper insights into demand and supply patterns, thereby adding value through informed decisions (Irfan & Wang, 2019).

As a data-driven decision science, management accountancy is likely to gain much from BDA through the prompt availability of required inputs for various decision-making processes. Big data is increasingly used in accounting to process information for actionable insights with speed and accuracy (Elawadly, 2026; Munir et al., 2022). Richins et al. (2017) opine that big data will rewrite the profile of accountants. Management accounting is critically modifying every facet of a company's business success, and management accountants need to take the lead in technology adoption (Rikhardsson & Yigitbasioglu, 2018). Aghakishi (2023) argues that management accounting will increasingly depend on leveraging big data and other emerging technologies to drive strategic insights and operational efficiency. Therefore, management accountants have to be able to understand big data analytics and communicate its outcomes. With technological advancement, the focus of management accountants' jobs will shift away from human existence and working mechanisms. Innovations have shifted the focus of management accountants from just being strategic advisors to being strategic partners in the business arena (Ramachandran, 2019; Varma, 2018). This shift is fundamental and transformative; therefore, the integration of technology and strategic thinking needs to align with the role of management accountants in a data-driven era. The new, innovative data sources present opportunities and challenges for all professionals working with data and information, including management accountants (Tiron-Tudor & Deliu, 2021). Findings from Spraakman et al. (2021) highlight the expanding role of management accountants in decision-making due to their data analytics capabilities. However, management accountants have not reaped the full benefits from it. Analytical activities are still confined to the descriptive level only. Researchers also highlighted the behavioural aspects of technology diffusion in business-related domains. Schmidt et al. (2020) found that some accounting professionals are not moving beyond Excel and are resisting the adoption of new analytics technologies. Attitude and subjective norm are significant antecedents of management accountants' intent to use big data technologies (Varma, 2018).

Business operations have transformed with the use of BDA in decision-making. As a fast-growing economy, India is witnessing rapid digitalization across sectors, backed by technological infrastructure, technical literacy, and digital governance. The IT-enabled business ecosystem has created enormous opportunities to integrate BDA into the management accounting domain (Karina et al., 2025). The technological disruptions such as BDA, machine learning, and artificial intelligence in finance have significantly altered the dynamics of traditional management accounting practices, including budgeting, cost control, auditing, performance management, and strategic decision-making. Management accountants are now expected to perform more strategic and data-oriented roles. Therefore, it becomes critical for management accountants to shift their roles from transactional tasks, such as bookkeeper, scorekeeper, accountant, and auditor, to data-oriented decision roles. On the governance front, the Institute of Cost Accountants of India (ICMAI) is the only statutory professional body in India to regulate the cost and management accountancy profession. As the highest-cost and management professional body in the world, the ICMAI has taken various advanced initiatives to embrace emerging technologies such as business analytics, big data analytics, and artificial intelligence in cost and management accounting practices. This includes updating curricula, conducting workshops, seminars, webinars, short-term courses, and similar events to build the capacity of management professionals.

Research momentum in 'big data analytics' began in 2016. Aldossari et al. (2023) conducted a systematic literature review. They found a maximum of 16 studies on this theme in 2021, followed by a downward trend until 2017, after which only one study was found in 2016. Varma et al. (2021) pointed out the growing academic interest in the 'big data and accounting' theme, particularly in auditing activities; however, BDA adoption in management accounting is a very little explored subject. The empirical research work on the 'big data analytics and management accounting' theme, particularly in the Indian context, is missing in the reputed indexed databases. This motivates us to explore the adoption of big data analytics by Indian management accountants in their working practices. This research seeks to investigate a comprehensive set of structural factors that affect BDA adoption across technological, organizational, and environmental contexts. The outcome of this work has practical implications for organizations, business managers, management accountants, technology solution providers, and other interested stakeholders, encouraging them to act instrumentally to drive wider adoption of BDA in management accountancy and to leverage technology-enabled, data-driven decision-making opportunities. More precisely, our work is a novel effort to investigate the significance of factors influencing BDA adoption among professional management accountants, using quantitative data in the Indian context. Utilizing primary responses from experienced professional cost and management accountants, the study will draw on the theoretical foundation of the TOE framework and state-of-the-art PLS-SEM, implemented in open-source R, to examine the factors influencing BDA adoption from the perspective of Indian management accountants. This whole work is divided into six sections. After conducting an extensive literature review in Section 2, Section 3 shall provide a detailed methodological description under 'method and material'. Section 4 presents a detailed analysis of the data and results. The results will be discussed in Section 5. Finally, the conclusion is presented in Section 6, which discloses limitations, theoretical and practical implications, and directions for future research.

LITERATURE REVIEW

The Internet of Things (IoT), Industrial Internet of Things (IIoT), Information and communication technologies (ICT), and economic data storage alternatives such as cloud computing have facilitated the generation and storage of big data at the enterprise level (Dai et al., 2020). Big data analytics refers to the use of advanced techniques and capabilities to analyse and visualise large datasets. Five analytical methods were described by Sivarajah et al. (2017), namely descriptive analytics for

reviewing history; inquisitive analytics attempts to find the reason for historical happenings; a step ahead, predictive analytics peeks into future happenings; and, finally, prescriptive and pre-emptive analytics concurrently intervene in the ecosystems to achieve desired results. BDA has emerged as an important topic in both the academic and business communities due to promising opportunities for improved business performance and value creation (Barnes et al., 2022; Chen et al., 2012; Gandomi & Haider, 2015). Previous researchers have studied BDA adoption from multiple perspectives and with respect to intentions. The central argument in the literature is that adopting BDA helps organizations unlock hidden value, improve performance, and achieve a competitive advantage (Danielsen et al., 2021). Both short- and long-term business objectives may be attained through BDA adoption (Zhu et al., 2021). Management accountants play a pivotal role in data-driven decision-making at both organizational and individual levels. Their responsibilities include guiding strategic choices, enabling process optimisation, and providing actionable information utilising data. For stewardship accounting, planning, MIS development, process optimization, internal controls, and various strategic decisions, management accountants dedicate significant effort to data acquisition, analysis, and inference. Access to high-quality, real-time accounting and costing information is crucial for making impactful financial and non-financial decisions. Accordingly, BDA adoption may empower management accountants to intervene effectively in information ecosystems, thereby supporting calibrated business outcomes.

Reflecting forward thinking, management accountants (MAs) have shifted their orientation from strategic advisor to strategic business partner within organizations (Varma, 2018). MAs are used to perform basic and advanced analytics on traditional structured datasets. However, big data analytics capabilities integrate semi-structured and unstructured datasets to provide actionable insights in real time. Richins et al. (2017) argue that BDA complements and supplements the management accountants' skills and knowledge, and that they are well positioned to play a pivotal role in problem-driven analytics of unstructured data sets. Therefore, MAs must utilize BDA's capabilities in decision science. Spraakman et al. (2021) suggest that management accountants have not expanded beyond the descriptive nature of analysis, deploying complex models and integrating both external and internal operational data; thus, BDA opportunities remain underutilized. According to a survey by Schmidt et al. (2020), some accounting professionals were comfortable with basic traditional data analytics tools but resistant to moving beyond Excel and adopting newer technologies such as BDA.

The impact of BDA on management accounting is transformative; however, integrating big data analytics into management accounting practices entails several technical, organisational, environmental, ethical, and behavioural issues that organisations must address (Aghakishi, 2023). The adoption of BDA depends on several factors, including skill set, training, ease of use, expected effort, performance expectancy, organizational culture, regulatory regime, concerns about potential job losses, and accidental data exposure. The perceptions and readiness of management accountants towards BDA adoption are influenced by technical and other external factors (Grosu et al., 2023). Every new technology comes with great merits over existing technology, but always suffers from a few demerits. There has been a constant struggle with the BDA benefits and barriers that prevent its adoption. Therefore, knowing which factors encourage and prevent management accountants from using BDA is essential to address them effectively and promptly.

The empirical relationship between BDA adoption and organizations and firms (including SMEs) has been examined by previous researchers (Alquhaif & Al-Mamary, 2025; Babalghaith & Aljarallah, 2024; Gangwar, 2018; Lai et al., 2018; Lutfi et al., 2022; Verma & Chaurasia, 2019). The adoption of BDA in the auditing function was examined by Saud et al. (2025) and Abdelwahed et al. (2025). Vysotskaya and Prokofieva (2025) examined technology acceptance in management accountancy from the educational perspective. Studies suggest that Indian organisations are increasingly utilising data analytics tools to improve performance through data-driven strategic planning. Findings by Sarbhai and Khare (2024) underscore the importance of BDA capabilities in managerial decision-making. Indian organizations experienced a positive influence of BDA capability on strategic planning, thereby improving firm performance (Begum & Rahman, 2026). Dubey et al. (2022) examined the role of BDA capabilities in achieving competitive advantage by Indian service-sector MSMEs. The findings emphasize that BDA capabilities can help medium and small firms achieve sustainable competitiveness, especially in uncertain business conditions such as the COVID-19 pandemic. Bag et al. (2022) identified critical technological and organizational barriers that influence technology adoption in Indian manufacturing supply chains. These works have addressed critical issues and enriched the theoretical and knowledge bases; however, very limited attention has been given to explaining how these challenges affect core management practices such as budgeting, cost management, Internal controls, and managerial reporting mechanisms. Further, due to the rapid evolution of big data, machine learning, and artificial intelligence, management accounting professionals must possess analytical and technological competencies to support predictive and prospective decision analysis (Renu & Goyal, 2026). This fundamental shift in the role of management accountants underscores the immediate need to conduct empirical studies to examine Indian management accountants' perspectives on the adoption of BDA.

The fundamental elements of the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) were utilized. TOE comprehensively integrates internal and external variables and frameworks, which is readily reconcilable with diffusion of innovation theory. The TOE framework integrates environmental and societal characteristics of technology, thereby providing a holistic picture independent of organizational size and location (Sharma et al., 2023). Aldossari et al. (2023), in a systematic literature review, found that TOE was the most dominant theory used in BDA adoption studies, followed by TAM, UTAUT, Resource-Based Theory, and DOI. TOE is an extremely popular and widely used theory in technology adoption studies for its ability to measure theoretical and psychological factors (Aldossari et al., 2023). Although other models, such as TAM, TAM2, DOI, and UTAUT, are regularly used by researchers in the technology adoption phenomenon, they have certain limitations. For example, TAM mainly focuses on individual usefulness and ease; it ignores organizational factors. TAM2 is an individual-centric model that primarily focuses on user acceptance; it also considers social influence, but it remains largely individual-focused. DOI overemphasises its innovation while

overlooking the organisational context. Therefore, the TOE is the most suitable model due to the greater weightage of the organizational dimension relative to individuals' attributes, especially for gauging BDA adoption among Indian management accountants. Drawing on the literature and context, this study proposes the conceptual model shown in Figure 1.

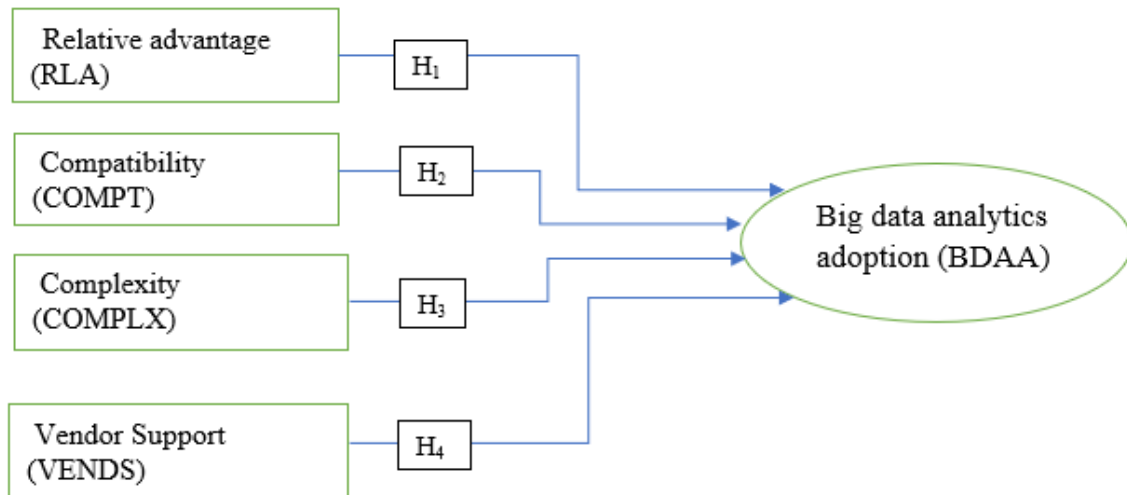


Figure 1. Conceptual Model

Source: Authors' Own Creation

The adoption of big data analytics in management accounting work practices is a technological application. The technological context in the adoption study is a very critical aspect as it incorporates both endogenous and exogenous elements (Maroufkhani et al., 2020). One widely used technical factor is relative advantage. Rogers (2003) defines relative advantage as the degree to which the adoption of new technology is perceived as superior to prevailing technology. Relative advantage addresses the organisational intention to adopt technology, which is primarily driven by perceived improvements in organisational performance (Baker, 2012; Kapoor et al., 2015). The advantages of new technology over existing technology can be one reason for BDA adoption by management accountants.

Organizations operate in pursuit of a targeted mission through a complex network of physical and virtual resources. The fit between organizations' existing technology and prospective technology significantly influences the adoption decision (Salleh et al., 2015). Compatibility refers to the extent to which the new technology is perceived as aligned with an organization's existing practices and infrastructure. With respect to BDA technology adoption in management accounting work, an organization should evaluate the compatibility of the proposed technology with its infrastructure and workforce technical capabilities, and ensure that management provides the necessary support for compatible technologies (Maroufkhani et al., 2020). In general, compatibility is a technical factor; to a great extent, compatibility associated with BDA adoption in management accounting is an organizational factor. This is because cost and management accounting data are strategic assets of organizations and, unlike financial information, are not publicly available. In the Indian regulatory regime, cost records and cost audit are mandated for a certain class of companies. The costing and associated management accounting records and audit findings are used by stakeholders, including the government, for pricing decisions and policy interventions. Besides this, the organizations use this information for various decision-making purposes. Therefore, prospective technology must be compatible to accommodate current and future dynamics. Prior researchers empirically established compatibility as a significant influential factor (Chen et al., 2015; Gangwar, 2018; Kapoor et al., 2015; Verma & Bhattacharyya, 2017).

The adoption process for newer technology might fail if users perceive it as too difficult to understand and use (Rogers, 2003). Complexity associated with technology is a key factor in the adoption process. Complexity is the degree to which an innovation is difficult to understand and apply. Complex technological innovations are not appreciated by users even though they are superior to existing ones (Lutfi et al., 2022). From a generic user's viewpoint, it is expected that the newer technology can be learned easily and should have few similarities to the existing one. Complexity is negatively associated with BDA adoption in previous research (Gangwar, 2018; Lai et al., 2018; Maroufkhani et al., 2020). Overcomplexity creates a dilemma, and users are less likely to adopt BDA if they perceive it as complex.

In the BDA adoption process, the external environment plays a crucial role. Organizations always focus on their core products or services to establish unique selling propositions. To adopt technical innovations like BDA, organizations need immediate external technical support to understand the true merit of newer technology solutions for their businesses. Demonstration of BDA capabilities on a free trial basis and after-sales services at a reasonable cost are genuine expectations from vendors. Vendors providing BDA-related technical solutions must critically evaluate distinct business complexities to offer a tailored solution to the parties. Merely generic solutions cannot be translated to solve a working problem with normal efforts (Caesarius & Hohenthal, 2018). BDA service providers and vendors should critically analyse the target organisations' current environment and data practices to develop BDA tools and customised plans (Yadegaridehkordi et al., 2018). Specific support from vendors or third parties encourages organizations to adopt BDA (Gangwar, 2018). Management accountants deal with strategically oriented data within an organization, as well as data from various clients, in their roles as practitioners

or consultants. Therefore, data security is of utmost importance, especially when using third-party tools or publicly accessible servers. BDA tools installed by vendors must have robust data security checkpoints that align with organizational data security policies and regulatory standards. Technical support with data security assurance is likely to encourage management accountants to adopt BDA.

Knowing the relative importance of each factor discussed will help develop appropriate strategies. Stakeholders can appreciate their roles and responsibilities once it is empirically established how a factor influences BDA adoption, which is crucial for the data-rich accounting domain of 'Management accounting'. Against this backdrop, we propose the following hypotheses.

H₁: The relative advantage of BDA positively influences its adoption.

H₂: A higher degree of compatibility positively influences BDA adoption.

H₃: A higher level of complexity involved in BDA is negatively associated with BDA adoption.

H₄: There is a positive relation between vendor support and BDA adoption.

MATERIALS AND METHODS

Based on items used in similar previous studies, the survey instrument was prepared (Table I). These items were modified to suit the study's context. Before floating the instrument for actual data collection, the survey questionnaire was exposed to four industrial experts and two practitioners engaged in management accountancy and data-related domains for their opinions and comments. One language expert was also invited to improve the instrument's face. Experts' feedback included adding, altering, deleting, and inter-construct swapping of a few items. This calibration of the instrument is necessary owing to the novelty of the study's context. Incorporating the suggestions and comments from experts, the questionnaire was designed on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). After a pilot study, the final instrument was deployed for final data collection.

Table 1. Items Reference Sources

Factor	Short name	Description	Reference sources
Relative Advantage	RLA	Superiority of innovation over existing ones.	(Gangwar et al., 2015; Lutfi et al., 2022; Maroufkhani et al., 2020; Sharma et al., 2023)
Compatibility	COMPT	Innovation can accommodate existing features, processes and resources.	(Akter et al., 2016; Aldossari et al., 2023; Gangwar, 2018; Ghaleb et al., 2023; Lutfi et al., 2022)
Complexity	COMLX	Abstract measure of the difficulty of using and understanding an innovation from users' viewpoint.	(Kapoor et al., 2015; Lutfi et al., 2022; Maroufkhani et al., 2020)
Vendor Support	VENDS	Third parties to extend support and encouragement for adopting and using an innovation.	(Gangwar, 2018; Maroufkhani et al., 2020)

Source: Authors' compilation

This study targets Indian cost and management accountants working in industry or practising the cost and management accountancy domain. To ensure a high-quality sample, only professionally qualified cost and management accountants (CMAs) from The Institute of Cost Accountants of India (ICMAI) with at least 4 years of work experience were included in the study. Several reasons have been identified for selecting this population type. Only this professional body has statutory status and power to regulate the cost accountancy profession in India. Two, the CMA course delivery mechanism is a blend of a rigorous academic curriculum and practical training modules in industry and at practising firms. Three, CMAs practise cost management accountancy in the public domain or have a substantial say in the decision-making process of any organization. Fourth, the population is geographically spread over India. As the population in this study is homogeneous with sufficient working experience of the subject, the sample size can be worked out by following the statistical relationship (Kumar et al., 2013; Tambuskar et al., 2024)

$$\text{Sample size} = Z^2 \times p \times (1-p) / H^2 \quad (\text{x denote multiplication sign})$$

At a 95% confidence level, the value of $Z = 1.96$ (normal distribution table); p is the estimated proportion of the population that presents the characteristics; $p = 0.5$ can be used as a conservative value; higher or lower values yield a smaller required sample size; and H = margin of error (10% or 0.10). Applying the above formula, sample size = $(1.96)^2 \times 0.5(1-0.5) / (0.1)^2 = 96.04$. Thus, a minimum of 96 completed questionnaires is required. Using email networks, public directories, and personal contact, a form was circulated via a mobile Whacollector to collect responses from 400 potential respondents. This was followed by two gentle reminders, each at one-week intervals. In the Google Form, all fields were marked mandatory, so there was no scope for missing values or incomplete responses. A total of 242 responses were collected for utilization in this study.

The hypothesized model was tested using the Structural Equation Modeling-Partial Least Squares (SEM-PLS) method through R programming. There are several reasons to consider PLS-SEM and R programming. PLS-SEM is a multivariate statistical technique that enables the estimation of complex relationships among multiple exogenous and endogenous constructs within a single model. Unlike CB-SEM (covariance SEM), which requires normally distributed data, PLS-SEM is quite robust to skewness and kurtosis. Compared to CB-SEM, PLS-SEM can obtain a solution with a smaller sample size (Hair & Alamer, 2022). There is an increasing trend in the use of PLS-SEM in social science research (Hair & Alamer, 2022; Hair et al., 2011, 2018, 2019, 2021). R is open-source, free software, and can be downloaded from the

Comprehensive R Archive Network (CRAN) for various operating systems (R Core Team, 2024). The setup of R and RStudio enables researchers to write code in the R console and view both textual and graphical output simultaneously. The R programming language is becoming the preferred choice of researchers. We used the SEMinR package (Ray et al., 2020) for PLS-SEM to test the relationship.

In PLS literature, the measurement and structural models are referred to as the outer and inner models, respectively (Hair & Alamer, 2022). The theoretical model in this study is formed from reflective constructs (construct points towards its items); therefore, the assessment of the outer model includes estimation of loadings and p-values, estimation of indicator reliability and internal consistency, obtaining the average variance extracted (AVE) for convergent validity, and checking for discriminant validity using HTMT (Hair et al., 2020). Once the reliability and validity of indicators and constructs are established, the inner (structural) model is tested for collinearity. This follows the evaluation of path significance and the assessment of the coefficient of determination R^2 . The next section provides a detailed assessment of the inner and outer models.

RESULTS

Table 2 presents the demographic profile of 242 respondents.

Table 2. Respondents' profile

Variables	Category	Frequency	Percentage
Working Environment	Industry	197	81.40
	Practicing	45	18.60
Experience (years)	4-9	82	33.88
	10-14	73	30.16
	>=15	87	35.96
Age (years)	< 30	15	12.40
	30-39	132	54.55
	40-49	62	25.62
	> 50	33	07.43

Source: Authors' Compilation

The data for this study were collected through a self-administered online single-respondent survey. To rule out the possibility of common method bias, a single-factor Harman test (Harman, 1967; Tehseen et al., 2017) was performed. Podsakoff et al. (2003) suggest that data are free from bias if the first construct explained variance is greater than 50%. The first factor accounted for 44% of the total variance, which is well below the recommended threshold of 50%. Thus, the results of Harman's test confirm that common method bias is not a problem in this study.

Owing to differences in underlying theories, each measurement has distinct assessment conditions. While assessing the quality of the reflective measurement model, both reliability and validity are evaluated at the indicator and construct levels. The very first step is to examine indicator reliability, which measures the variance of an indicator explained by its construct. The acceptable value of the loadings is greater than 0.708, indicating that the construct explains more than 50% of the variance in the indicators. The loading values placed in Table III are well above the threshold of 0.708, and the indicators are reliable.

Table 3. Indicators' Loading

ITEMS	RLA	COMPT	COMPLX	VENDS	BDAA
RLA1	0.866	0.000	0.000	0.000	0.000
RLA2	0.852	0.000	0.000	0.000	0.000
RLA3	0.796	0.000	0.000	0.000	0.000
RLA4	0.849	0.000	0.000	0.000	0.000
RLA5	0.752	0.000	0.000	0.000	0.000
RLA6	0.803	0.000	0.000	0.000	0.000
RLA7	0.738	0.000	0.000	0.000	0.000
RLA8	0.800	0.000	0.000	0.000	0.000
COMPT1	0.000	0.755	0.000	0.000	0.000
COMPT2	0.000	0.779	0.000	0.000	0.000
COMPT3	0.000	0.819	0.000	0.000	0.000
COMPT4	0.000	0.762	0.000	0.000	0.000
COMPT5	0.000	0.780	0.000	0.000	0.000
COMPT6	0.000	0.788	0.000	0.000	0.000
COMPT7	0.000	0.769	0.000	0.000	0.000
COMPT8	0.000	0.800	0.000	0.000	0.000
COMPLX1	0.000	0.000	0.795	0.000	0.000
COMPLX2	0.000	0.000	0.833	0.000	0.000
COMPLX3	0.000	0.000	0.828	0.000	0.000
COMPLX4	0.000	0.000	0.808	0.000	0.000
COMPLX5	0.000	0.000	0.760	0.000	0.000
COMPLX6	0.000	0.000	0.785	0.000	0.000
VENDS1	0.000	0.000	0.000	0.784	0.000
VENDS2	0.000	0.000	0.000	0.835	0.000
VENDS3	0.000	0.000	0.000	0.866	0.000
VENDS4	0.000	0.000	0.000	0.861	0.000

VENDS5	0.000	0.000	0.000	0.837	0.000
VENDS6	0.000	0.000	0.000	0.796	0.000
BDAA1	0.000	0.000	0.000	0.000	0.856
BDAA2	0.000	0.000	0.000	0.000	0.883
BDAA3	0.000	0.000	0.000	0.000	0.904
BDAA4	0.000	0.000	0.000	0.000	0.885

Source: R output, Authors' Compilation

Internal consistency is evaluated by three measures: Cronbach's alpha (alpha), Composite reliability (rhoC), and reliability coefficient (rhoA) (Pereira et al., 2024). As a rule of thumb, the values of (alpha) and (rhoC) should be greater than 0.7; values above 0.95 are problematic. Reliability values of 0.95 or higher also suggest that the indicators are redundant and that there is a problem with the response pattern. The value of the coefficient (rhoA) lies between conservative Cronbach's alpha and rhoC. The reliability values in Table 3 meet-3 meet the criterion and fall within the 'satisfactory to good' range (Hair et al., 2021). Convergent validity (equivalent to the communality) was assessed using the average variance extracted (AVE). Table IV shows that all AVE values are greater than 0.50; therefore, the constructs explain more than 50% of the variance in their respective indicators (Hair et al., 2022).

Table 4. Constructs' Reliability

ITEMS	alpha	rhoC	AVE	rhoA
RLA	0.924	0.938	0.653	0.928
COMPT	0.909	0.926	0.611	0.911
COMPLX	0.889	0.915	0.643	0.890
VENDS	0.910	0.930	0.689	0.912
BDAA	0.905	0.934	0.779	0.906

Source: R Output, Authors' compilation

To establish the distinctiveness of reflectively measured constructs in the model, discriminant validity was evaluated using the widely accepted Fornell and Larcker (1981) criterion (FL) and the heterotrait–monotrait ratio of correlations (HTMT) criterion. The FL matrix is presented in Table V, where the diagonal values (sqrt of AVE) are greater than the off-diagonal values corresponding to the row and column. FL criteria are satisfied, and the constructs are distinct from each other.

Table 5. Fornell and Larcker's Criterion

TEMS	RLA	COMPT	COMPLX	VENDS	BDAA
RLA	0.808	.	.	.	.
COMPT	0.772	0.782	.	.	.
COMPLX	0.393	0.391	0.802	.	.
VENDS	0.562	0.602	0.307	0.830	.
BDAA	0.766	0.742	0.340	0.624	0.882

Source: R Output, Authors' Compilation

Some research work questions the reliability of FL criteria in empirical applications. Henseler et al. (2015) established through simulations that FL, particularly SEmInR, is not a reliable measure of discriminant validity and becomes inconsistent with slight changes in indicator loadings. Thus, a better measure of discriminant validity, the heterotrait–monotrait ratio of correlations (HTMT), has been evaluated. A general threshold of HTMT < 0.90 and a conservative limit of < 0.85. In Table VI, HTMT values are well below the conservative threshold, indicating that the model's constructs are conceptually distinct.

Table 6. HTMT ratio

ITEMS	RLA	COMPT	COMPLX	VENDS	BDAA
RLA	.	.	.	.	.
COMPT	0.834	.	.	.	.
COMPLX	0.433	0.432	.	.	.
VENDS	0.613	0.660	0.342	.	.
BDAA	0.832	0.813	0.378	0.685	.

Source: R output, Authors' Compilation

Further, a bootstrapping procedure (n = 1000, bootstrap subsamples) was performed, and the resulting bootstrap confidence intervals are presented in Table VII. While performing bootstrapping, the significance level was set to 0.10 (default = 0.05) using the *alpha* argument. Doing so, 90% two-sided bootstrap confidence intervals (equivalent to 5% one-tailed) for the HTMT values were obtained.

Table 7. Bootstrapped_HTMT

ITEMS	Original Estimates	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
RLA -> COMPT	0.834	0.831	0.043	19.472	0.753	0.893
RLA -> COMPLX	0.433	0.428	0.100	4.341	0.256	0.587
RLA -> VENDS	0.613	0.610	0.066	9.225	0.496	0.714
RLA -> BDAA	0.832	0.827	0.044	18.706	0.750	0.891
COMPT -> COMPLX	0.432	0.427	0.096	4.494	0.265	0.585
COMPT -> VENDS	0.660	0.658	0.062	10.601	0.546	0.753
COMPT -> BDAA	0.813	0.809	0.046	17.775	0.729	0.878
COMPLX -> VENDS	0.342	0.341	0.096	3.565	0.184	0.495
COMPLX -> BDAA	0.378	0.373	0.104	3.622	0.189	0.536
VENDS -> BDAA	0.685	0.685	0.062	10.992	0.577	0.780

Source: R Output, Authors' Compilation

The bootstrap confidence interval in Table 7 above demonstrates the discriminant validity of the constructs in the model. After establishing the reliability and validity of the constructs, the structural model was evaluated. The model was evaluated for collinearity with the variance inflation factor (VIF). Hair et al. (2021) suggest that collinearity is not an issue if $VIF < 3$. The VIF values ranged from 1.636 to 2.794, well below the threshold limits (Table 8). This indicates that the model is free from collinearity problems.

Table 8. VIF Antecedents

BDAA:	RLA	COMPT	COMPLX	VENDS
	2.62	2.794	1.215	1.636

Source: R output, Authors' Compilation

In addition, the causal connections between the constructs were examined. This involves evaluating path coefficients to assess the significance and relevance of the paths. Path significance assessment relies on bootstrapping standard errors to calculate *t*-values for path coefficients. A path coefficient is said to be significant at the 5% level if the value zero does not fall within the 95% confidence interval. Typically, path coefficients > 0.20 are considered significant. Also, the value of bootstrapped T-statistic estimates (T Stat.) should be greater than 1.960.

Table 9. Bootstrapped Structural Paths

Hypothesis	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI	Decision
RLA -> BDAA (H ₁)	0.428	0.422	0.07	6.14	0.298	0.531	Supported
COMPT -> BDAA (H ₂)	0.286	0.286	0.073	3.913	0.164	0.404	Supported
COMPLX -> BDAA (H ₃)	-0.005	-0.002	0.042	-0.116	-0.067	0.071	Not supported
VENDS -> BDAA (H ₄)	0.212	0.215	0.065	3.274	0.108	0.322	Supported

Source: R Output, Authors' Compilation

In Table 9, the original estimates, T-stat, 5% CI, and 95% CI values provide the paths' strength and significance levels for the hypotheses. It can be concluded that RLA has a strong positive impact on BDAA (0.422). Similarly, COMPT and VENDS have significant positive influences on BDAA, with path coefficients of 0.286 and 0.212, respectively. In contrast, the path coefficient of COMPLX -> BDA is just -0.005, with T-Stat = -0.166. It can be observed that the value zero falls between the 5% and 95% CIs. Accordingly, H₁, H₂ and H₄ are supported, and H₃ is rejected. Finally, the coefficient of determination was evaluated. The coefficient of determination (R^2) assesses the explained variance in the dependent (endogenous) constructs attributable to all independent (exogenous) constructs. R^2 (also called in-sample predictive power) is a measure of the explained variance in endogenous constructs caused by exogenous constructs. The explanatory power of the model for the endogenous construct (BDAA) yielded $R^2 = 0.671$ and $AdjR^2 = 0.666$ (Table-X). Referring to the recent guidelines, Hair et al. (2021) categorized predictive power as substantial (0.75), moderate (0.50), and weak (0.25) based on R^2 values. Accordingly, the predictive power of this model is very close to the substantial category. Figure 2 shows indicator loadings, path coefficients, R^2 , and path significance at the 5% and 95% CI levels.

Table 10. Paths' Explanatory Power

ITEMS	BDAA
R^2	0.671
$AdjR^2$	0.666
RLA	0.428
COMPT	0.286
COMPLX	-0.005
VENDS	0.212

Source: R output, Authors' Compilation

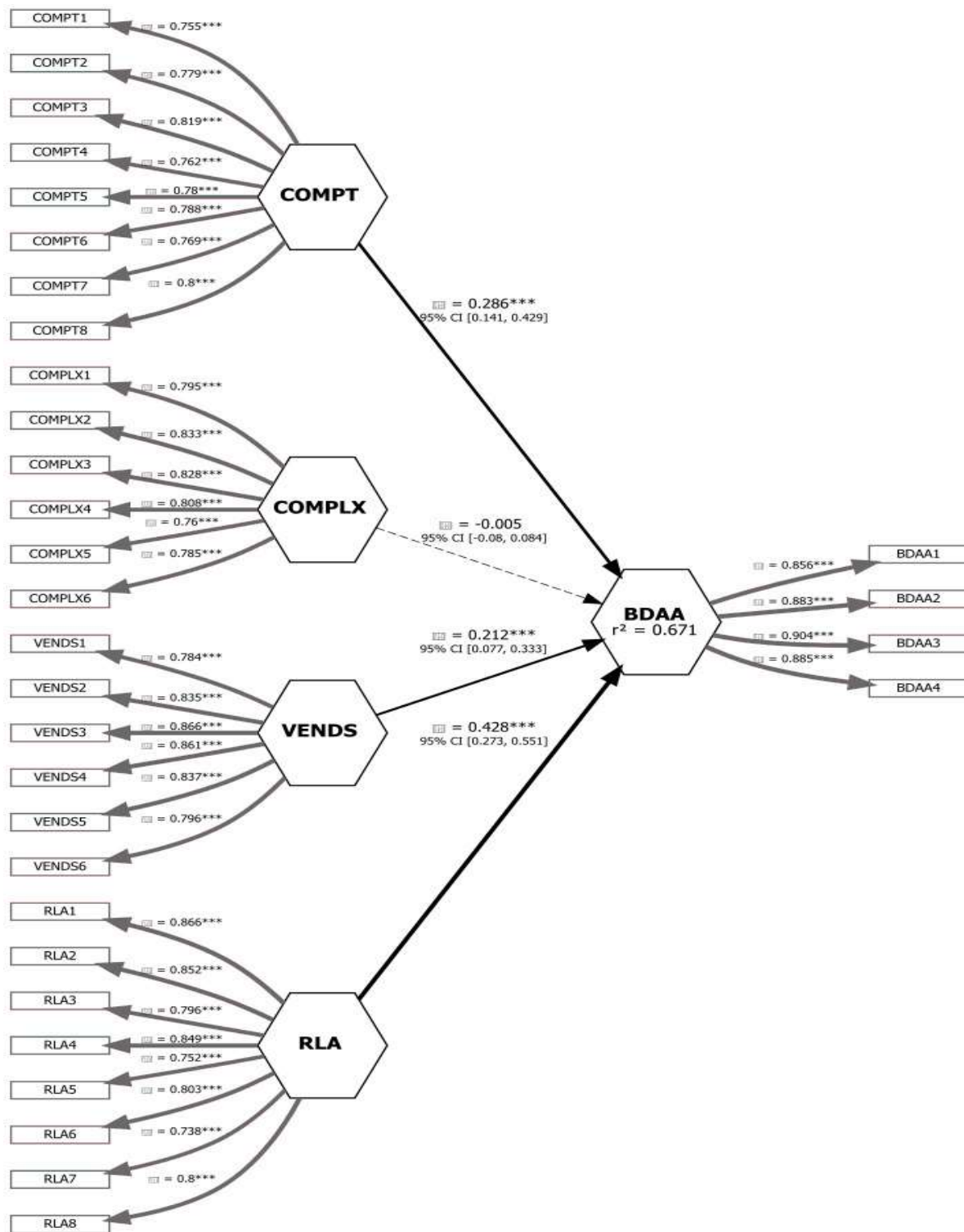


Figure 2. Model Graphics: Factor Loadings, Path Coefficients, Explanatory Power and Confidence Levels
Source: Output from R

DISCUSSIONS

Findings: This work indicates that relative advantage, compatibility, and vendor support are statistically significant factors in the adoption of BDA among Indian professional management accountants. Results support these findings and support the developed hypotheses H_1 , H_2 and H_4 . Relative advantage has emerged as the strongest predictor of BDA adoption. This confirms that relative advantage positively and significantly influences BDA adoption by virtue of its superiority over existing analytical technologies. The finding is in line with previous research, such as Al-Shanableh et al. (2024), Ghaleb et al. (2023), Lutfi et al. (2022), and Yadegaridehkordi et al. (2018). It can be inferred here that BDA is a useful tool for management accountants and may improve decision-making. It is suggested that management accountants should leverage BDA capabilities in decision science to write vibrant business success stories.

Compatibility of the existing system with BDA technology was positively associated with BDA adoption. This extends the arguments of prior research works conducted in different contexts (Akter et al., 2016; Aldossari et al., 2023;

Gangwar, 2018; Ghaleb et al., 2023; Kapoor et al., 2015; Verma & Bhattacharyya, 2017). Adopting good data management and governance practices, streamlining and smoothing organizational processes, adopting open standards, and upskilling the workforce are a few suggestions to enhance BDA compatibility (Mukherjee et al., 2025).

The third hypothesis, i.e. 'complexity involved in BDA technology negatively influences BDA adoption', was not supported by statistical numbers and hence rejected. This is an interesting finding that departs from several prior works (Lutfi et al., 2022; Maroufkhani et al., 2020). However, it supports the argument of Richins et al. (2017), which showed that accountants are already masters at working with structured data and well-positioned to create value in a BDA environment. Complexity associated with BDA technology was not found to be a critical issue for Indian CMAs. This may be due to the updated CMA course curricula on relevant academic and practical data analytics modules at different stages. Also, the early introduction of professional programmes, seminars, webinars, workshops, and short-term courses on advanced data analytics, artificial intelligence, and related subjects by ICAI for its students and members could be a key enabler of such capabilities. CMAs are conversant with traditional and some advanced-level data analytics tools as part of their day-to-day work. Furthermore, the respondents in this study have at least 4 years of post-qualification industrial and professional experience. This substantial tenure might have provided them with adequate technical competencies to effectively navigate and implement advanced data analytics technologies such as BDA.

As established by previous researchers, vendor support is critical and positively influences BDA adoption (Gangwar, 2018; Maroufkhani et al., 2020). Our results align with this argument. Vendors (third-party technology solution providers) may encourage clients to innovate and adopt BDA by providing customized, appropriate warranty terms, security assurances, free trials, training, workshops, and reliable after-sales services. Demonstration of BDA capabilities by vendors for solving specific business problems may help business managers to appreciate BDA adoption. Vendors and clients can critically examine the specific business needs, and vendors may offer workable solutions.

CONCLUSIONS

Considering the importance of big data analytics (BDA) in management accounting and its slow pace of adoption, as noted by the research community, we empirically examined positive and negative factors influencing BDA adoption from the viewpoints of Indian cost and management accountants. The findings of the work provide useful insights for managers, industry, governments, regulators, practitioners, professionals, and academicians. BDA is a superior technology compared with the analytical tools currently used by management accountants. To support the shift in the role of management accountants from strategic advisor to strategic partner in business, it is suggested that management accountants adopt BDA. Compatibility of existing IT infrastructure is a key factor; thus, BDA-compatible industries/firms can easily switch to BDA platforms. Additionally, a clear mandate from senior management at the organizational level is critical to the smooth adoption of BDA. However, complexity with BDA was not observed; it was a key hurdle in BDA adoption. Still, management accountants need continual upskilling to stay abreast of technological developments in data-driven decision science. Management accountants must continually update themselves to remain relevant in a disruptive technological environment and contribute value to the value chain. Technology partners (vendors) must play a crucial role in BDA adoption by providing customized, cost-effective plans. Vendors can offer demonstrations, free trials, security assurances, and resorbable after-sales services to tap into business opportunities.

Theoretically, this study enriched the limited block of BDA literature in the management accounting domain. Although previous researchers have performed BDA adoption and related studies targeting various themes such as SMEs, manufacturing, supply-chain, hotels, healthcare, auditing, education, etc., to the best of the authors' knowledge, none of the studies exclusively focus on management accountancy and management accountants working in different organizations in a fast-developing economy. As management accountants are uniquely positioned by virtue of their inbuilt analytical capabilities on structured data and exploratory analysis, drawing direct inferences from previous research may be inappropriate. For example, in most studies, complexity was a significant negative factor in BDA adoption, but our research does not support these findings. This work presents a robust theoretical model on the TOE framework with high exploratory power.

From a practical viewpoint, this study offers important implications for management accountants, BDA vendors, professional bodies, and other interested stakeholders. By understanding the critical factors for BDA adoption, one can appreciate why management accountants have lagged in adopting BDA and devise appropriate strategies to address the hindrances. BDA is a relatively superior analytical tool that can help management accountants improve decision-making. As a focused empirical study, the findings stress that BDA is a highly useful tool for management accountants and that they must adopt it in their management accounting practices. Management accountants are likely to gain significantly from adopting BDA in data-driven decision science. The compatibility between IT infrastructure and human attributes at the organizational level is a key issue, and BDA adoption will depend on top management mandate, IT department support, and a skilled workforce. Organizations should create a positive environment that facilitates the integration of physical and intellectual resources to ensure the smooth adoption of BDA in management accounting. BDA vendors should critically evaluate the need for BDA tools for management accountants and offer customized solutions with attractive pricing plans based on services or user count. To help visualize and appreciate the BDA benefits, vendors can offer a trial version with adequate training and technical support. Appropriate marketing strategies, such as positive word-of-mouth, social media marketing, referrals, deferred billing plans, security and privacy assurances, and free warranties, may enhance vendors' reputation and acceptance. Vendors may also demonstrate prior success stories of BDA adoption to attract new clients.

Interestingly, the complexity involved in BDA is not a critical issue for CMAs. However, there shall be a need for continual skill upgradation. The Indian professional accounting regulatory bodies, such as ICAI and ICAI, should periodically review and adapt the training modules in their main and short-duration courses. Individually, the technology

can be learned through short-term courses, workshops, seminars, webinars, and similar offerings from professional bodies, academic institutions, and vocational training providers. Apart from this, the National Programme on Technology Enhanced Learning (NPTEL) platform can be utilized to learn the BDA-related skills. There are several open-source/free platforms/forums from which management accountants can acquire relevant BDA skills. The management accountant must pass on the benefits of technological leverage to their clients and society at large by providing cost-effective, high-quality services.

Like any other empirical study, this study is not free from limitations. Generalizations of the results from this study require further support from similar studies, as the sample was limited to CMAs in India. As this is a cross-sectional study utilizing a questionnaire, a causal relationship cannot be ruled out. Longitudinal research can assess more precise and reliable results. Furthermore, to gain a deeper understanding of the topic, a qualitative inquiry is desirable.

Author Contributions: Conceptualization, V.K.; Methodology, V.K.; Software, V.K.; Validation, V.K.; Formal Analysis, V.K.; Investigation, V.K.; Resources, V.K.; Data Curation, V.K.; Writing –Original Draft Preparation, V.K.; Writing –Review & Editing, V.K.S.; Visualization, V.K.; Supervision, V.K.S.; Project Administration, V.K.S.; Funding Acquisition, V.K.S. Authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study because the research does not involve vulnerable groups or sensitive issues.

Funding: The authors received no direct funding for this research.

Acknowledgements: The authors have no acknowledgements to declare.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process: During the preparation of this work, the author(s) used Grammarly for proofreading and spell checking since the Authors are not native speakers. All intellectual content, analysis, and interpretations were produced solely by the authors. After using this AI tool/service, the author(s) reviewed and edited the content as needed, taking full responsibility for the publication's content.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

- Abdelwahed, A. S., Abu-Musa, A. A., Badawy, H. A., & Moubarak, H. (2025). Unleashing the beast: The impact of big data and data analytics on the auditing profession—Evidence from a developing country. *Future Business Journal*, 11(1), 1–18. <https://doi.org/10.1186/s43093-024-00420-7>
- Aghakishi, A. (2023, December 6). *Big data in management accounting*. SSRN. <https://ssrn.com/abstract=4718516>
- Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113–131. <https://doi.org/10.1016/j.ijpe.2016.08.018>
- Aldossari, S., Mokhtar, U. A., & Abdul Ghani, A. T. (2023). Factors influencing the adoption of big data analytics: A systematic literature and experts review. *SAGE Open*, 13(4), 1–25. <https://doi.org/10.1177/21582440231217902>
- Alquhaif, A. S., & Al-Mamary, Y. H. (2025). Examining factors influencing the adoption of accounting information systems: An analysis of behavioral intentions and usage behavior. *Human Systems Management*, 44(3), 401–420. <https://doi.org/10.1177/01672533241297453>
- Al-shanableh, N., Alzyoud, M., Alomar, S., Kilani, Y., Nashnush, E., Al-Hawary, S., & Al-Momani, A. (2024). The adoption of big data analytics in Jordanian SMEs: An extended technology–organization environment framework with diffusion of innovation and perceived usefulness. *International Journal of Data and Network Science*, 8(2), 753–764. <https://doi.org/10.5267/j.ijdns.2024.1.003>
- Babalghaith, R., & Aljarallah, A. (2024). Factors affecting big data analytics adoption in small and medium enterprises. *Information Systems Frontiers*, 26(6), 2165–2187. <https://doi.org/10.1007/s10796-024-10538-2>
- Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2022). Big data analytics: Implementation challenges in Indian manufacturing supply chains. *Computers in Industry*, 125, Article 103368. <https://doi.org/10.1016/j.compind.2020.103368>
- Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12
- Barnes, S. J., Guo, Y., & Chan, J. (2022). Big data analytics for sustainability: Insight through technological innovation. *Information & Management*, 59(5), Article 103627. <https://doi.org/10.1016/j.im.2022.103627>
- Begum, F., & Rahman, M. M. (2026). Impact of strategic management accounting on firm's financial performance: Evidence from Bangladesh's manufacturing sector. *International Journal of Accounting & Finance Review*, 17(1), 1–14. <https://doi.org/10.46281/ijafr.v17i1.291>
- Caesarius, L. M., & Hohenthal, J. (2018). Searching for big data: How incumbents explore a possible adoption of big data technologies. *Scandinavian Journal of Management*, 34(2), 129–140. <https://doi.org/10.1016/j.scaman.2017.12.002>
- Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, 32(4), 4–39. <https://doi.org/10.1080/07421222.2015.1138364>
- Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165–1188. <https://doi.org/10.2307/41703503>

- Dai, H.-N., Wang, H., Xu, G., Wan, J., & Imran, M. (2020). Big data analytics for manufacturing internet of things: Opportunities, challenges and enabling technologies. *Enterprise Information Systems*, 14(9–10), 1279–1303. <https://doi.org/10.1080/17517575.2019.1633689>
- Danielsen, F., Olsen, D., & Framnes, V. A. (2021). Toward an understanding of big data analytics and competitive performance. *Scandinavian Journal of Information Systems*, 33(1), 155–192.
- Dubey, R., Bryde, D. J., Foropon, C., Tiwari, M., & Dwivedi, Y. K. (2022). Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19. *Journal of Business Research*, 148, 378–389. <https://doi.org/10.1016/j.jbusres.2022.05.009>
- Elawadly, H. S. H. (2026). Comprehensive analysis of digitalization in management accounting: A bibliometric and coding analysis. *Journal of Financial Reporting and Accounting*. Advance online publication. <https://doi.org/10.1108/JFRA-01-2025-0002>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Fortune Business Insights. (2025). *Big data technology market size, share & industry analysis, 2025–2032*. <https://www.fortunebusinessinsights.com/big-data-technology-market-100144>
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137–144. <https://doi.org/10.1016/j.ijinfomgt.2014.10.007>
- Gangwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. *Information Resources Management Journal*, 31(4), 1–22. <https://doi.org/10.4018/IRMJ.2018100101>
- Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM–TOE model. *Journal of Enterprise Information Management*, 28(1), 107–130. <https://doi.org/10.1108/JEIM-08-2013-0065>
- Ghaleb, E. A. A., Dominic, P. D. D., Singh, N. S. S., & Naji, G. M. A. (2023). Assessing the big data adoption readiness role in healthcare between technology impact factors and intention to adopt big data. *Sustainability*, 15(15), Article 11521. <https://doi.org/10.3390/su151511521>
- Grosu, V., Cosmulese, C. G., Socoliuc, M., Ciubotariu, M. S., & Mihaila, S. (2023). Testing accountants' perceptions of the digitization of the profession and profiling the future professional. *Technological Forecasting and Social Change*, 193, Article 122630. <https://doi.org/10.1016/j.techfore.2023.122630>
- Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), Article 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110. <https://doi.org/10.1016/j.jbusres.2019.11.069>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature. <https://doi.org/10.1007/978-3-030-80519-7>
- Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., & Menictas, C. (2019). Partial least squares structural equation modeling-based discrete choice modeling: An illustration in modeling retailer choice. *Business Research*, 12(1), 115–142. <https://doi.org/10.1007/s40685-018-0072-4>
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. <https://doi.org/10.2753/MTP1069-6679190202>
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced issues in partial least squares structural equation modeling*. Sage.
- Harman, H. H. (1967). *Modern factor analysis*. University of Chicago Press.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Irfan, M., & Wang, M. (2019). Data-driven capabilities, supply chain integration and competitive performance: Evidence from the food and beverages industry in Pakistan. *British Food Journal*, 121(11), 2708–2729. <https://doi.org/10.1108/BFJ-02-2019-0131>
- Jackson, D., Michelson, G., & Munir, R. (2023). Developing accountants for the future: New technology, skills, and the role of stakeholders. *Accounting Education*, 32(2), 150–177. <https://doi.org/10.1080/09639284.2022.2057195>
- Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2015). Empirical examination of the role of three sets of innovation attributes for determining adoption of IRCTC mobile ticketing service. *Information Systems Management*, 32(2), 153–173. <https://doi.org/10.1080/10580530.2015.1018776>
- Karina, R., Siti-Nabiha, A. K., & Jurnal, T. (2025). Big data integration in performance management and control: A socio-technical perspective. *Journal of Accounting & Organizational Change*, 22(2), 313–332. <https://doi.org/10.1108/JAOC-07-2024-0238>
- Kumar, S., Luthra, S., & Haleem, A. (2013). Customer involvement in greening the supply chain: An interpretive structural modeling methodology. *Journal of Industrial Engineering International*, 9(1), Article 6. <https://doi.org/10.1186/2251-712X-9-6>

- Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics adoption in logistics and supply chain management: An empirical investigation. *The International Journal of Logistics Management*, 29(2), 676–703. <https://doi.org/10.1108/IJLM-06-2017-0153>
- Lutfi, A., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Alshira'h, A. F., Alshirah, M. H., Saad, M., & Ibrahim, N. (2022). Factors influencing the adoption of big data analytics in the digital transformation era: Case study of Jordanian SMEs. *Sustainability*, 14(3), Article 1802. <https://doi.org/10.3390/su14031802>
- Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, 54, Article 102190. <https://doi.org/10.1016/j.ijinfomgt.2020.102190>
- Mukherjee, A., Sharma, U., & Liu, J. (2025). Big data analytics role in shaping the work of accounting function and accounting professionals. *Journal of Accounting & Organizational Change*, 21(7), 272–295. <https://doi.org/10.1108/JAOC-08-2024-0255>
- Munir, S., Abdul Rasid, S. Z., Aamir, M., Jamil, F., & Ahmed, I. (2022). Big data analytics capabilities and innovation: Effect of dynamic capabilities, organizational culture and role of management accountants. *Foresight*, 25(1), 41–66. <https://doi.org/10.1108/FS-08-2021-0161>
- Pereira, L. M., Sanchez Rodrigues, V., & Freires, F. G. M. (2024). Use of partial least squares structural equation modeling (PLS-SEM) to improve plastic waste management. *Applied Sciences*, 14(2), Article 628. <https://doi.org/10.3390/app14020628>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Ramachandran, R. (2019). Big data analytics and the management accountant. *The Management Accountant Journal*, 54(5), 40–43. <https://doi.org/10.33516/maj.v54i5.40-43>
- Ray, S., Danks, N. P., & Velasquez-Estrada, J. M. (2020). *semnr: Domain-specific language for building and estimating structural equation models* (Version 2.3.7) [R package]. <https://cran.r-project.org/web/packages/semnr/>
- Renu, & Goyal, N. (2026). Impacts of artificial intelligence and big data analytics on accounting practices and professional roles. *International Journal of Research in Commerce and Management Studies*, 8(1), 585–606.
- Richardson, V., Teeter, R., & Terrell, K. (2019). *Data analytics for accounting*. McGraw-Hill Education.
- Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). Big data analytics: Opportunity or threat for the accounting profession? *Journal of Information Systems*, 31(3), 63–79. <https://doi.org/10.2308/isyss-51805>
- Rikhardsson, P., & Yigitbasiglu, O. (2018). Business intelligence and analytics in management accounting research: Status and future focus. *International Journal of Accounting Information Systems*, 29, 37–58. <https://doi.org/10.1016/j.accinf.2018.03.001>
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Salleh, K. A., Janczewski, L. J., & Beltrán, F. (2015). SEC-TOE framework: Exploring security determinants in big data solutions adoption. In *Proceedings of the Pacific Asia Conference on Information Systems (PACIS 2015)* (Paper 203). Association for Information Systems. <https://aisel.aisnet.org/pacis2015/203>
- Sarbhay, A., & Khare, V. (2024). Leveraging big data for enhanced strategic planning and improved firm performance: A study of Indian organizations. *Metamorphosis*, 23(1), 77–89. <https://doi.org/10.1177/09726225241249525>
- Saud, I. M., Sofyani, H., Utami, T. P., Mukhlis, M., & Fathmaningrum, E. S. (2025). Big data analytics-based auditing adoption in public sector: Indonesian evidence. *Cogent Business & Management*, 12(1), Article 2454320. <https://doi.org/10.1080/23311975.2025.2454320>
- Schmidt, P. J., Riley, J., & Swanson Church, K. (2020). Investigating accountants' resistance to move beyond Excel and adopt new data analytics technology. *Accounting Horizons*, 34(4), 165–180. <https://doi.org/10.2308/HORIZONS-19-154>
- Sharma, M., Gupta, R., Sehrawat, R., Jain, K., & Dhir, A. (2023). The assessment of factors influencing big data adoption and firm performance: Evidences from emerging economy. *Enterprise Information Systems*, 17(12), Article 2218160. <https://doi.org/10.1080/17517575.2023.2218160>
- Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research*, 70, 263–286. <https://doi.org/10.1016/j.jbusres.2016.08.001>
- Spraakman, G., Sanchez-Rodriguez, C., & Tuck-Riggs, C. A. (2021). Data analytics by management accountants. *Qualitative Research in Accounting & Management*, 18(1), 127–147. <https://doi.org/10.1108/QRAM-11-2019-0122>
- Tambuskar, D. P., Jain, P., & Narwane, V. S. (2024). An exploration into the factors influencing the implementation of big data analytics in sustainable supply chain management. *Kybernetes*, 53(5), 1710–1739. <https://doi.org/10.1108/K-07-2022-1057>
- Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences*, 4(2), 142–168. <https://doi.org/10.20547/jms.2014.1704202>
- Tiron-Tudor, A., & Deliu, D. (2021). Big data's disruptive effect on job profiles: Management accountants' case study. *Journal of Risk and Financial Management*, 14(8), Article 376. <https://doi.org/10.3390/jrfm14080376>
- Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
- Varma, A. (2018). Big data usage intention of management accountants: Blending the utility theory with the theory of

- planned behavior in an emerging market context. *Theoretical Economics Letters*, 8(13), 2803–2817. <https://doi.org/10.4236/tel.2018.813176>
- Varma, A., Piedepalumbo, P., & Mancini, D. (2021). Big data and accounting: A bibliometric study. *The International Journal of Digital Accounting Research*, 21(27), 203–238. https://doi.org/10.4192/1577-8517-v21_8
- Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of big data analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management*, 30(3), 354–382. <https://doi.org/10.1108/JEIM-10-2015-0099>
- Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. *Information Resources Management Journal*, 32(3), 1–26. <https://doi.org/10.4018/IRMJ.2019070101>
- Vysotskaya, A., & Prokofieva, M. (2025). Management accounting and data analytics: Technology acceptance from the educational perspective. *Accounting Education*, 34(3), 410–433. <https://doi.org/10.1080/09639284.2024.2338140>
- Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A., & Ibrahim, O. (2018). Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL-ANFIS approach. *Technological Forecasting and Social Change*, 137, 199–210. <https://doi.org/10.1016/j.techfore.2018.07.043>
- Zhu, S., Dong, T., & Luo, X. (2021). A longitudinal study of the actual value of big data and analytics: The role of industry environment. *International Journal of Information Management*, 60, Article 102389. <https://doi.org/10.1016/j.ijinfomgt.2021.102389>

Publisher's Note: American Accounting & Finance Society stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



© 2026 by the authors. Licensee of the American Accounting & Finance Society, USA. This open-access article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

International Journal of Accounting & Finance Review (P-ISSN 2576-1285 E-ISSN 2576-1293) by American Accounting & Finance Society is licensed under a Creative Commons Attribution 4.0 International License.